



THE UNIVERSITY *of* EDINBURGH

Edinburgh Research Explorer

## The Effects of Mean Wind Speed Uncertainty on Project Finance Debt Sizing for Offshore Wind Farms

### Citation for published version:

Borràs mora, E, Spelling, J, Van Der Weijde, A & Pavageau, E-M 2019, 'The Effects of Mean Wind Speed Uncertainty on Project Finance Debt Sizing for Offshore Wind Farms', *Applied Energy*, vol. 252. <https://doi.org/10.1016/j.apenergy.2019.113419>

### Digital Object Identifier (DOI):

[10.1016/j.apenergy.2019.113419](https://doi.org/10.1016/j.apenergy.2019.113419)

### Link:

[Link to publication record in Edinburgh Research Explorer](#)

### Document Version:

Peer reviewed version

### Published In:

Applied Energy

### General rights

Copyright for the publications made accessible via the Edinburgh Research Explorer is retained by the author(s) and / or other copyright owners and it is a condition of accessing these publications that users recognise and abide by the legal requirements associated with these rights.

### Take down policy

The University of Edinburgh has made every reasonable effort to ensure that Edinburgh Research Explorer content complies with UK legislation. If you believe that the public display of this file breaches copyright please contact [openaccess@ed.ac.uk](mailto:openaccess@ed.ac.uk) providing details, and we will remove access to the work immediately and investigate your claim.





---

# The Effects of Mean Wind Speed Uncertainty on Project Finance Debt Sizing for Offshore Wind Farms

Esteve Borràs Mora<sup>1,2\*</sup>, James Spelling<sup>3</sup>, Adriaan H. van der Weijde<sup>4</sup>,  
Ellen-Mary Pavageau<sup>2</sup>

<sup>1</sup> Industrial Doctoral Centre for Offshore Renewable Energy (IDCORE), The University of Edinburgh, Edinburgh, EH9 3JL, UK

<sup>2</sup> EDF Energy R&D UK Centre, Interchange, 81-85 Station Road, Croydon, CR0 2AJ, UK

<sup>3</sup> EDF Energy, 90 Whitfield Street, London, W1T 4EZ, UK

<sup>4</sup> School of Engineering, University of Edinburgh, and The Alan Turing Institute, London. Faraday Building, The King's Buildings, Mayfield Road, Edinburgh EH9 3DW

## Abstract

Financing costs for offshore projects depend, among many other variables, on the quality of mean wind speed predictions. Financial institutions determine the amount of debt that can be reasonably supported by the project, based on probabilistic cash flow metrics derived from estimated mean wind speeds. Within the offshore wind industry, it is widely believed that longer wind resource campaigns or more precise wind measurement devices that decrease mean wind speed uncertainty lead to lower Levelised Cost of Energy (LCOE) values. This paper shows that this is not always true, while a decrease in mean wind speed uncertainty may result in better financing conditions, it typically requires higher development expenditure. We build a theoretical cost modelling framework, which includes detailed project financing constraints, and then apply this to an industrial case study to analyse project financing of different types of offshore wind farms. We show that developers need to find the right balance between a decrease in financing costs and an increase in development expenditure. For projects limited by the maximum gearing or with an unfavourable trade-off between the development expenditure and the increased P90 annual energy production, more precise resource estimation can result in higher LCOE values. This paper suggests a new way of understanding the effects of wind resource assessment campaigns by integrating project finance constraints into cost calculations and highlighting the importance of detailed cost modelling for optimal design of offshore wind farms.

**Keywords:** Offshore wind project finance, wind speed uncertainty, decision-making processes under uncertainty

---

\*Corresponding author.  
Email: E.Borras-Mora@ed.ac.uk.  
Tel: +44 (0)7470 023 829

---

## Abbreviations

**AEP** Annual Energy Production

**AEP<sub>P50</sub>** Annual Energy Production based on P50 estimated mean wind speed

**AEP<sub>P90</sub>** Annual Energy Production based on P90 estimated mean wind speed

**BHHMM** Below Hub Height Met Mast

**CAPEX** Capital Expenditure

**CFADS** Cash Flow Available for Debt Service

**DECEX** Decommissioning Expenditure

**DEVEX** Development Expenditure

**DSCR** Debt Service Coverage Ratio

**EPCM** Engineering Procurement and Construction Management

**FCF** Free Cash Flows

**FID** Final Investment Decision

**FLIDAR** Floating Light Detection and Ranging

**HAFLIDAR** High Accuracy Commercial Floating LIDAR

**HHMM** Hub Height Met Mast

**HVAC** High Voltage Alternating Current

**IAV** Inter-annual Variability

**LAFLIDAR** Low Accuracy Commercial Floating LIDAR

**LCOE** Levelised Cost of Energy

**NPV** Net Present Value

**O&M** Operations and Maintenance

**OPEX** Operational Expenditure

**OWCAT** Offshore Wind Cost Analysis Tool

**SPV** Special Purpose Vehicle

# 1 Introduction

The importance of project finance for renewable energy projects has been highlighted in [1]. It is understood that project finance could be instrumental in increasing the availability of capital for a successful energy transition, of which offshore wind projects could benefit from. Large-scale offshore wind is often developed through stand-alone project companies, owned by the project investors. A project company, also referred to as a Special Purpose Vehicle (SPV), has its own revenues and balance sheet and therefore the ability to raise funding on its own merits. An SPV can raise two discrete categories of funding: equity and debt. In this paper, project finance, or non-recursive financing, is considered for the development of offshore wind farms. As the offshore wind industry grows and more banks are involved in non-recourse financing for offshore wind farms [2, 3, 4], a better understanding of how wind farms are financed and what the banks' requirements are, is needed. The financial terms offered by the lenders and the ability of the offshore wind farm to meet its financial obligations once operational depend, among many other variables, on uncertain wind-driven revenues. Given the fact that wind power varies with the cube of the wind speed, accurately and precisely determining the wind speed is of utmost importance for both developers and their bankers during the project's planning stage.

Consider a developer that wants to raise money from a bank or another financial institution in order to build an offshore wind farm. If all goes well and the project succeeds, the bank will have the loan repaid with interest. If the project exceeds its performance and generates more revenues than expected, the bank does not take any benefit from additional production - it has limited upside risk. On the contrary, if the project under-performs then the bank can lose up to the full value of the loan - it has full downside risk. Given that the bank has a limited upside but is exposed to a larger downside, it usually puts in place several mitigation measures to control the project risks, one of which is a comprehensive analysis of the wind resource assessment uncertainty. This is typically carried out before the Final Investment Decision (FID) and it requires a sound understanding of the uncertainty of the wind speed and energy losses in order to estimate the potential size of the debt funding that can be reasonably supported by the cash flows of the project. Generally speaking, if the bank is satisfied with the level of confidence with which the yield has been evaluated, it might regard the value as a low uncertainty estimate and provide access to higher gearings, i.e. a higher proportion of finance that is provided by debt relative to the finance provided by equity. Since the cost of debt is cheaper than the cost of equity, developers always try to maximize the share of debt. Developers may therefore need to find the right balance between an increase in the development expenditure associated with better wind speed predictions and a decrease in the financing costs to minimise their LCOE.

The effects of mean wind speed uncertainty in project finance for offshore wind farms were first investigated in the work of Schreider [5]. A high-level study was conducted to select the optimal contract strategy for investing in an offshore wind project. Even though the study slightly touched upon mean wind speed uncertainty by considering a downside scenario with P84 instead of the P50 yield in one of the business cases, the study did not go further; it can be considered as a simple downside scenario analysis. However, wind risk has been identified as one of the fundamental pieces of technical due diligence for project finance offshore wind farms [6]. In addition, offshore wind research has devoted considerable efforts to characterise the uncertainty associated with the annual energy production, given by the inherent uncertainty in the resource as shown in [7, 8, 9] and the uncertainty in the technology [10].

Furthermore, offshore wind techno-economic models have been developed to offer a basis for objective communication and decision-making, allowing for a greater number of cases to be analysed and when considering new ideas, offering the option to assess the economic feasibility and potential. Examples of those can be found in [11, 12, 13, 14]. However, given the multidisciplinary nature of techno-economic modelling activities, studies tend to be either very detailed in the wind resource assessment part while ignoring financial valuation principles or they make use of sound financial models that do not take into consideration fundamental principles of wind resource assessment.

Thus, there is a research gap in the literature when it comes to bringing together the wind resource assessment uncertainty and bank requirements, which have a direct impact on project finance costs. No previous literature has attempted to explain how a reduction in mean wind speed uncertainty can be translated to both an increase in the development expenditure and a reduction in the cost of financing. It is the trade-off between these two ingredients that determines their aggregated contribution to LCOE. Moreover, no previous project finance model has been published in the literature where the relationship between the P50 and P90 estimated mean wind speed is explained. This lack of analysis is probably due to the limited access to detailed industrial cost models, combining enough technical and financial expertise to be able to carry out this study.

When developing an offshore wind farm a trade-off between the wind resource assessment uncertainty and the development expenditure has to be made. That is to say, the developer has to choose a commercial sensing device (e.g. meteorological mast or Floating Light Detection and Ranging (FLIDAR)) to deploy in order to characterize the wind resource in a given zone. The choice of one or another device determines the magnitude of the Development Expenditure (DEVEX) and the uncertainty in the wind speed measurement. Within the offshore wind industry, it is widely believed that longer wind resource campaigns or more precise wind measurement devices that decrease mean wind speed uncertainty lead to lower LCOE values. But is this always the case? In other words, does the deployment of additional advanced sensing technology, which presumably reduces wind speed uncertainty, compensate for the incurred development expenditure?

The current paper is a first attempt to answer these questions, and to include detailed project finance constraints in wind farm planning decisions. Our focus lies on quantifying the impact of mean wind speed estimated uncertainty reduction on the LCOE of offshore wind farms. Naturally, there are many other long-term uncertainties that influence the operational, economical and financial performance of the farm, but, since wind speeds are such a crucial determinant of wind farm performance, we will leave other uncertainties aside in our quantitative analysis; however, we will briefly describe and, where possible, quantify them before moving on. Throughout, we will also assume that the developer has a good track record of projects and that experienced contractors have been appointed; if this is not the case, banks may impose additional requirements beyond the scope of this paper before taking on any investment risk.

The contribution of this paper is the development of a novel theoretical cost modelling framework which includes, detailed considerations of financing requirements that until now have been usually ignored in the offshore wind planning models. The methodology presented here can be applied to any existing standard corporate finance cost model to account for project finance arrangements. At the same time, this cost modelling framework allows policy-makers and developers alike to assess the trade-off between DEVEX and the estimated wind speed uncertainty, leading to more informed decisions that have the potential to drive down the cost of energy.

The rest of this paper is organised as follows: Section 2 introduces the widely used concepts of P50, P90 and some fundamentals of project finance. Section 3 describes the offshore wind cost modelling tool and provides a high-level overview of its inputs, outputs and the interplay between them. Section 4 describes the formation of the financial module within the tool, which is a key ingredient to understand and quantify the effects of the estimated mean wind speed uncertainty in obtaining better financing conditions. Following this, engineering techniques and financial methods are brought together to understand the implications of the mean wind speed uncertainty reduction in the LCOE, as shown in Section 5. Finally, the findings of the paper are exemplified by an industrial case study throughout Section 6.

## 2 Project Finance for Offshore Wind Farms

The profits of an offshore wind project are wind-driven. Given the uncertain nature of the wind, developers use probabilistic metrics to characterise the wind resource at a given site. Annual Energy Production based on P50 estimated mean wind speed ( $AEP_{P50}$ ) is associated with a P50 estimated mean wind speed  $\overline{v_{P50}}$ , meaning that this is the mean wind speed that is expected to be exceeded in 50% of the estimates. It is important to highlight that this is the estimated mean wind speed and not the measured mean wind speed, which would follow a different probability distribution function such as Rayleigh or Weibull. To put it in other words, this is the median mean wind speed estimate since half of the estimates are expected to be below this value and the other half are predicted to be above it. Although this metric is typically considered from a developer's point of view when doing corporate finance, banks prefer a rather conservative approach; reasons for this are explained in Section 1. Thus, banks use the Annual Energy Production based on P90 estimated mean wind speed ( $AEP_{P90}$ ), which is the Annual Energy Production (AEP) associated with an estimated mean wind speed that is expected to be exceeded in 90% of the estimates  $\overline{v_{P90}}$ . The mean wind speed estimated uncertainty is assumed to be characterized by a normal probability distribution, as it is shown in the following relationship 1:

$$\overline{v_{PX}} = \overline{v_{P50}} - \sqrt{2} \cdot \sigma \cdot \text{erf}^{-1} [1 - 2 \cdot F_X] \quad \forall X \in [0, 100] \quad (1)$$

Where  $\sigma$  is the given level of uncertainty expressed as a percentage of the wind speed representing one standard deviation and  $X$  is the level of exceedance requested by the bank. In particular, when looking at a level of exceedance of 90% or P90, Equation 2 results in:

$$\overline{v_{P90}} = \overline{v_{P50}} - 1.2816\sigma \quad (2)$$

Figure 1 shows the relationship between a  $\overline{v_{P50}}$  of 9 m/s and its associated  $\overline{v_{P90}}$  for a given  $\sigma$  of 4%, 6%, and 8%. Reducing the uncertainty increases the  $\overline{v_{P90}}$  value as well as the  $AEP_{P90}$ .

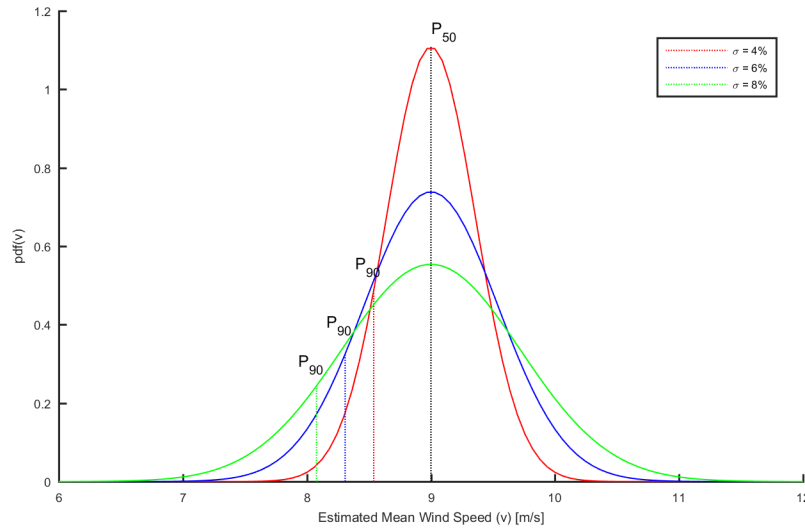


Figure 1: Relationship between P50 and P90 estimated mean wind speeds for different uncertainties

The AEP uncertainty, represented by its probability distribution function, is determined by propagating the mean wind speed estimated uncertainty together with the uncertainty in the energy factors. However, given the scope of the paper, the energy factors have been held constant throughout the study and considered as known techno-economic assumptions (for instance,  $X\%$  availability,  $Y\%$  wake effect losses,  $Z\%$  electrical losses). This means that the normality hypotheses assumed for the wind

speed uncertainty are not applied in the energy factors. In this way, the uncertainty is propagated from the mean wind speed to the AEP based on these known techno-economic assumptions.

Debt sizing determines the maximum amount of project finance debt that an offshore wind farm can sustain based on the banks' requirements. Project lenders usually determine the borrowing capacity on the basis of debt service ratios and covenants. Covenants are restrictions that specify certain limitations, such as the size and use of the loan. Financial institutions have to have an idea of the amount of debt that can be reasonably supported by the project and typically base their limitation on probabilistic metrics such as the P50 and P90 mean wind speed. That is the reason why uncertainty plays a key role in determining the amount of debt.

In project finance, the most common debt service ratios are the Debt Service Coverage Ratio and the maximum gearing. While the gearing is expressed as a percentage of the total project debt the owners are allowed to take on, the Debt Service Coverage Ratio (DSCR) is defined as the Cash Flow Available for Debt Service divided by the debt service (which is calculated as the principal  $P_{(t)}$  plus interest  $I_{(t)}$ ) for any given period  $t$ . DSCR metrics are typically used in private infrastructure project debt [15], in particular in offshore wind projects [16]. Financial institutions might then decide upon the lower debt size resulting out of the two debt-sizing techniques [17]. They also determine what Cash Flow Available for Debt Service (CFADS) is its mean wind speed estimate based on; typically a P50 or P90 mean wind speed. In this paper it is assumed that CFADS is based on P90 cash flows, that is to say, cash flows based on a P90 mean wind speed.

The notion of deriving the debt repayments together with the debt size in order to meet a single or multiple DSCR ratios is known as debt sculpting. When sculpting debt, principal repayments are being manipulated so that the total debt service matches the CFADS for any given period. As a consequence, the DSCR follows the desired target profile. By increasing the DSCR target, debt repayments are reduced in each period, but the last. As debt repayment are reduced, the span of time needed to fully repay the debt increases, which looks appealing from the sponsor point of view. On the other hand, lower DSCR targets increase repayments, resulting in the debt being repaid earlier. The limiting DSCR is given by the bank in conjunction with a constraint in the maximum gearing, since the debt has to be repaid within the debt tenor. When assuming a constant DSCR target, the following Equation 3 holds for every cash flow period  $t$ :

$$DSCR = \frac{CFADS_{(t)}}{P_{(t)} + I_{(t)}} \quad \forall t \quad (3)$$

From Equation 3, it is seen that, if this is true for every time period, the sum of the cash flows follows the relationship displayed in Equation 4, where  $k$  is the number of cash flow periods. Thus, by limiting the amount of gearing that a project can take on, a new DSCR is obtained, shown in Equation 5.

$$DSCR = \frac{\sum_{t=1}^k CFADS_{(t)}}{\sum_{t=1}^k P_{(t)} + \sum_{t=1}^k I_{(t)}} \quad (4)$$

$$DSCR = \frac{\sum_{t=1}^k CFADS_{(t)}}{\text{gearing} \cdot \text{debt service}} \quad (5)$$

This means that the minimum DSCR target used in the financial calculation should be the minimum of the one imposed by the bank, which we define as  $DSCR_1$ , and the one calculated based on Equation 5, which we define as  $DSCR_2$ . Therefore, the resulting DSCR of a project is displayed in Equation 6.

$$DSCR = \min(DSCR_1, DSCR_2) \quad (6)$$



If  $DSCR_2$  is higher than  $DSCR_1$ , the debt cannot be repaid before maturity; that is why the minimum of the two DSCRs is used in the financial calculation. For a developer, the lower the DSCR, the better the offshore wind investment is, as the DSCR measures how many times the cash flows after debt service can repay the scheduled debt service. The approach taken so far consisted in explaining how a limitation in the maximum gearing is reflected into the DSCR in order to be able to take the most restrictive covenant based on a DSCR criteria. This can also be done based on a gearing criteria. A maximum gearing is given by the bank, so we can now find an equivalent gearing given by a DSCR condition, following the same rationale explained in Equation 5. This relationship is shown in Equation 7.

$$gearing = \frac{\sum_{t=1}^k CFADS_{(t)}}{DSCR \cdot debt_{service}} \quad (7)$$

As a consequence, if we define the maximum gearing imposed by the bank as  $gearing_1$  and the maximum gearing given a DSCR condition based on Equation 7 as  $gearing_2$ , the resulting gearing for a project is obtained from the most restrictive covenant, shown in Equation 8.

$$gearing = \min(gearing_1, gearing_2) \quad (8)$$

In addition, bank requirements for different types of infrastructure asset classes such as offshore wind projects evolve with time. It is well understood that the risks involved when building, commissioning and operating an offshore wind project are reflected in the cost of capital. In this regard, the offshore industry has entered a maturation phase and a strong group of actors has emerged. These range from developers to independent power producers, from institutional banks to commercial banks, from suppliers of wind turbines to cables. Over the last few years, this strong group of actors has acquired experience and knowledge about what it takes to bring a project to commissioning or to deal with the marine construction risk. All of this supported by a strong track record of projects being delivered on time and on budget. As these risks are being better understood by the financial institutions and there is a strong track record of successful projects, the bank requirements are being reduced. This maturation phase of the sector is reflected in better financing conditions as shown in Table 1.

Period	Gearing	Maturity post-completion	Pricing
2006-2007	60:40	10-15 years	150-200 bps
2009-2011	65:35	10-15 years	300 bps
2012-2013	70:30	10-15 years	300-375 bps
2014-2015	70:30	10-15 years	200-250 bps
2016-2017	75:25	15-17 years	150-225 bps

Table 1: Typical project finance conditions for offshore wind farms from 2006 to 2017 [18]

Typical DSCR constraints are now 1.50 with P50 and 1.30 with P90. This arises from the fact that financial institutions see no or very limited price risk on the revenue side, a net availability in the 92-95% range, conservative Operations and Maintenance (O&M) cost assumptions and a full insurance package included [19].

### 3 Offshore Wind Cost Modelling Tool

The modelling approach to offshore wind cost analysis presented in this paper is based around the Offshore Wind Cost Analysis Tool developed at the EDF Energy R&D UK Centre [20]. This cost modelling tool has been used in the past for comparative evaluation of multiple sites, detailed evaluation of specific project layouts and sensitivity studies on both design/technology choices and cost variations. The tool has been validated against cost data from the Navitus Bay, Courseulles-sur-Mer and Neart na Gaoithe projects and shown to be accurate within  $\pm 15\%$  for these cases.

The model consists of three main modules: a wind farm design module, a cost calculation module and a financial module. The first stage of the module concerns the wind farm design. In order to evaluate the costs of the project, it is necessary to understand the number and type of wind turbines, foundations, inter-array cabling and the export system. In other words, the wind farm itself must be modelled. Designing an offshore wind farm requires interaction between teams from different disciplines; for example, the wind turbine team will have to interact with the foundation team to make sure that the loads of the turbine are correctly passed onto the foundation, and the foundation team will need to make sure that the electrical connections are correctly secured within the foundation. As such, a cost model must capture the same interactions as the design process and cannot be a simple accumulation of models from separate disciplines.

The design outputs of the first module are fed as inputs into the second module, which calculates the costs of the different offshore wind farm components. The cost module can be divided into DEVEX, Capital Expenditure (CAPEX), Operational Expenditure (OPEX) and Decommissioning Expenditure (DECEX). DEVEX covers the costs of all the processes up to the financial close or placing firm orders to proceed with wind farm construction. CAPEX calculates the supply and installation costs of the wind farm; including wind turbines, foundations, inter-array cables, offshore substations, export cables and onshore substations. Indirect costs such as Engineering Procurement and Construction Management (EPCM) costs and insurance are also included in the CAPEX breakdown. OPEX includes direct costs for the operation and maintenance of the wind farm, as well as transmission charges, insurance, taxes and royalties. DECEX accounts for the decommissioning of the wind turbines, foundations and offshore substations.

The cost outputs of the second module are passed into the third module, which accounts for the financial model of the wind farm project. The financial model takes into consideration the different cash flows throughout the life of the wind farm, as well as the financing structure put in place to supply the initial capital investment. Based on the resulting free cash flows and financing costs, the LCOE can be determined, together with other financial performance indicators. The financial module allows for corporate and project financing modelling.

The OWCAT input data structure is shown in Figure 2.

- (i) Project Specifications
- (ii) Technical Specifications
- (iii) Economic and Financial Specifications
- (iv) Vessel Specifications
- (v) Structural Masses and Electrical Components Database

(i) refers to the project offshore wind farm characteristics such as the capacity of the farm, the wind speed at a given referenced height, the average water depth, the soil conditions, the distance from shore, the wind turbine model, foundation type and export system specifications among others. Since no two projects have the same characteristics, project specifications attempt to model each particular site. (ii) addresses the details of the offshore wind technology, representing wind turbine, foundation, inter-array cable, export system and grid parameters. For example, as far as the wind turbine is concerned, parameters such as the wind turbine availability, the installation vessel associated with the wind turbine, the average loading, installation and commissioning times are accounted for. In addition, a decommissioning factor is used for all offshore wind farm components to account for a reduction in time from the installation phase. (iii) concerns the reference year for real prices, the risk-free rate and cost of debt, insurance and insurance premium tax rates, contingency requirements, corporation taxes, depreciation, seabed rent, exchange rates and inflation. (iv) involves the different vessel characteristics used in the installation and decommissioning of the offshore wind farms. As an example, heavy-lift jack-up vessel parameters would comprise of the day rate, vessel transit speed, vessel positioning time, vessel mobilisation time, operational weather window and carrying capacities in regard to different components. (v) consists of the data used to establish the foundation mass correlations, which are the basis for the CAPEX estimation in the foundation procurement. It also considers the correlations used to estimate the cost of different electrical components.

The final design contains not only the design of the offshore wind farm, where the foundations masses, inter-array and export system are sized, but also the procurement, vessel charter model and the AEP as displayed in Figure 2. Procurement stores all information concerning wind turbines, foundations and the electrical system, in terms of the type, number of elements and size (also length if required), giving rise to a procurement catalogue which forms the basis for the cost module. The vessel charter model is based on the work of Kaiser et al. [21], whereas the AEP is built upon industry's best practices assuming respectively either a logarithmic- or power-law wind profile in conjunction with a Rayleigh or Weibull probability distribution to model the wind speed. Wake losses and electrical losses are also accounted for in the AEP submodule.

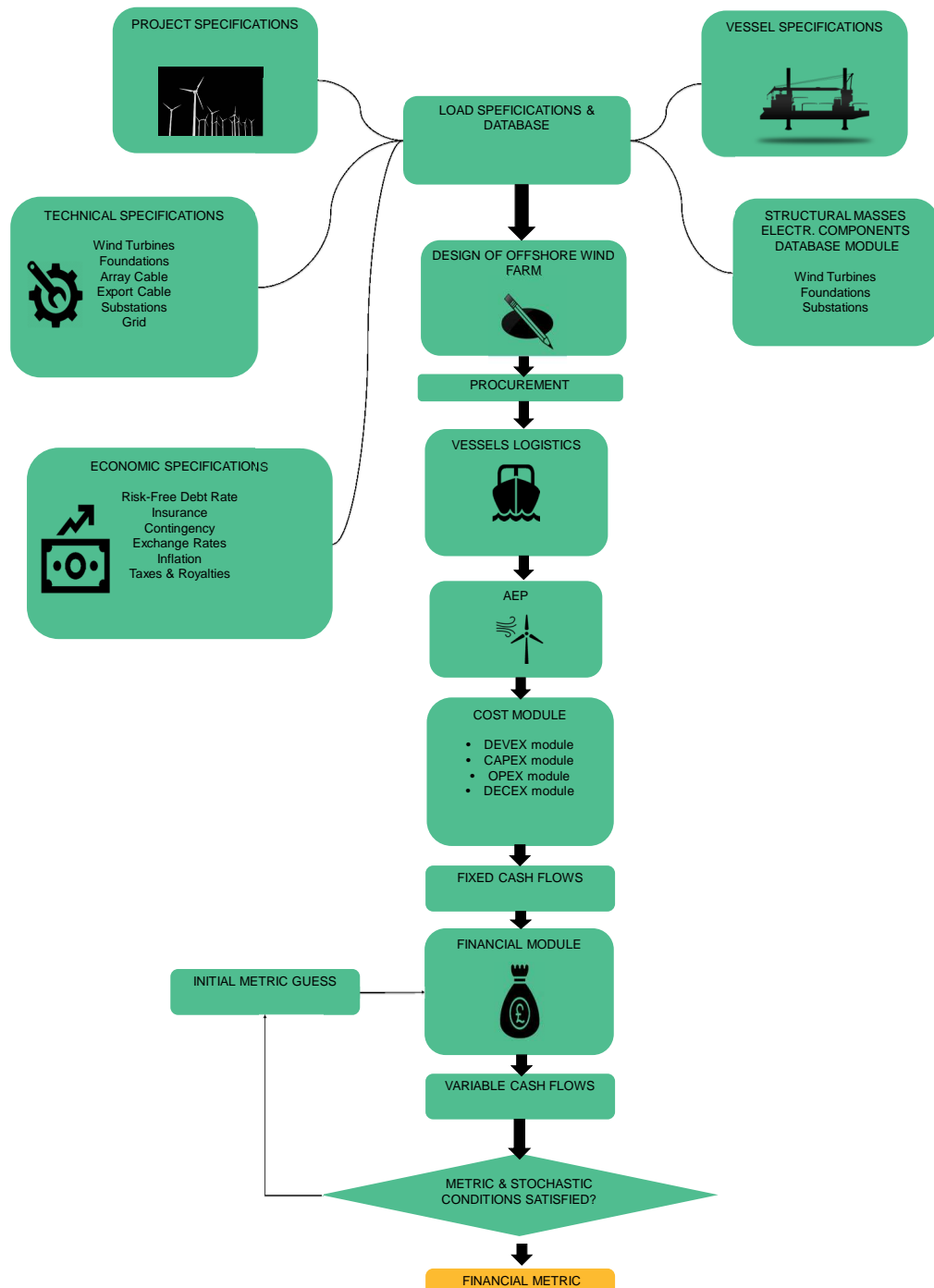


Figure 2: High Level Structure of Cost Modelling Tool

## 4 Formation of the Financial Module

As far as project evaluation is concerned, given a set of cash flows it is relatively easy to calculate several financial metrics such as the Net Present Value, Internal Rate of Return, Payback Period or Profitability Index. These financial metrics are worked out by projecting backwards in time a set of cash flows, resulting into its present value. In addition, they not only depend on the profile of the cash flows but also on a given discount factor.

A financial metric typically used in the energy sector to evaluate the financial performance of a project is the LCOE. The LCOE is a metric for which an equal-valued fixed revenue delivered over the life of the asset's generating profile would cause the project to break even. Equation 9 translates the LCOE definition into a mathematical formula, where TOTEX is the total expenditure and Net Present Value (NPV) is an operator which converts a set of cash flows to present value, given a discount rate. Bearing in mind that the discounted sum of the revenue cash flows should be equal to the discounted sum of expenditures, the right-hand side of Equation 9 is obtained. It is important to notice the fact that the LCOE is a constant value, and therefore,  $NPV(LCOE \cdot AEP) = LCOE \cdot NPV(AEP)$  and also that the revenue is expressed by  $LCOE \cdot AEP$  (in currency units) and accounts for the profit earned by electricity sales.

$$LCOE = \frac{NPV(TOTEX)}{NPV(AEP)} \rightarrow NPV(Revenue) = NPV(LCOE \cdot AEP) = NPV(TOTEX) \quad (9)$$

The financial module output of the cost modelling tool is the LCOE, which is a universal metric used for comparison of energy costs, and represents a single, constant, inflation-adjusted price available over the entire lifetime of the project, that also takes into consideration the full range of project cash flows based on its characteristics. The LCOE is used for decision making and is made up of Revenue and TOTEX cash flows. TOTEX can in turn be broken down into DEVEX, CAPEX, OPEX, and DECEX. If TOTEX would not depend on the LCOE, then the problem would be trivial and the left-hand side of Equation 9 would give us a methodology to work out the LCOE. However, this is not the case. Although DEVEX and DECEX are fixed items, and such can be assessed without any iterative method, CAPEX and OPEX comprise fixed and non-fixed costs, resulting in functions of the LCOE.

In other words, numerical techniques are needed to work out the LCOE. The first step to calculate the LCOE is to define the free cash flows. Although there is more than one way to define the Free Cash Flows (FCF), in this paper it is assumed that the FCF are calculated as the cash flow from operations minus the offshore wind farm's capital expenditures. In this way, the LCOE can be calculated by finding the zero of the function given by the sum of the discounted FCF, as shown in Equation 10.

$$FCF =_{def} LCOE \cdot AEP - TOTEX = 0 \rightarrow NPV(FCF) = 0 \quad (10)$$

The financial module consists of fixed and variable cash flows. Fixed cash flows are those that do not depend on the LCOE, whereas variable cash flows are a function of the LCOE. Therefore, whereas variable cash flows need to be recalculated at each iteration, fixed cash flows can be calculated only once at the beginning of the iterative process to improve the efficiency of the tool. Fixed cash flows are shown in Figure 3. DEVEX is displayed in red to highlight that different sensing devices will result in different development expenditure.

The financial appraisal for project finance arrangements entails not only one but twofold iterative processes. On the first hand, the external loop consists of determining the value of  $\lambda$  that makes Equation 11 equal to 0, where its initial guess  $\lambda_0$  is obtained from a simplified financial module. Each iteration

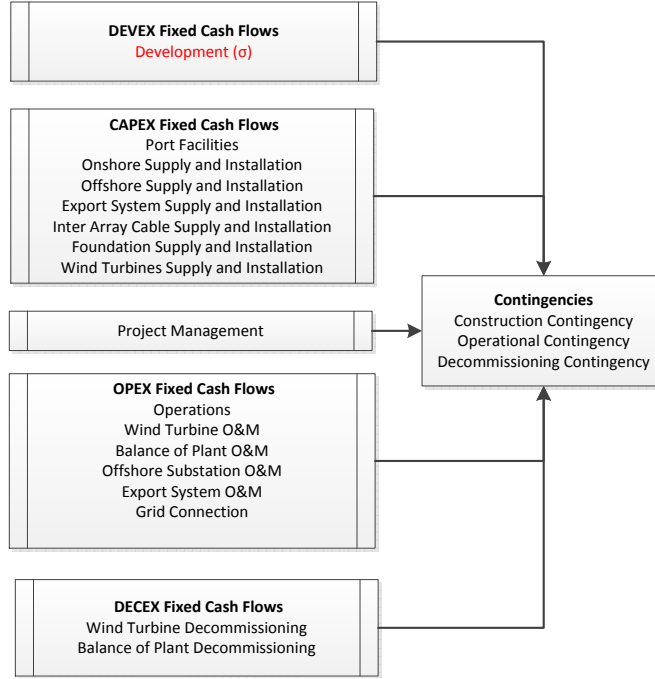


Figure 3: Fixed Cash Flows within Cost Modelling Tool

of the external loop is linked with an internal iterative process for debt sizing. The internal loop is only used for project finance arrangements and concerns the debt sizing or sculpting, which determines the maximum amount of project finance debt that the offshore wind farm can sustain based on the bank's requirements. Project lenders usually specify the borrowing capacity on the basis of debt service ratio and covenants. As such, parameters like the DSCR, the maximum leverage and CFADS have been considered. A priori, the variable  $\lambda$  is unknown, meaning that it will take several external and internal iterations to come up with the zero of Equation 11. In other words, the LCOE is calculated as the constant real electricity price required to meet the desired Minimum Acceptable Rate of Return, and not the other way around as usually considered. Given that it is inflation-adjusted, it means that a reference year must be defined (typically FID year is used).

$$LCOE = \lambda \left| \sum_{t=1}^n \frac{FCF_t(t)}{(1 + MARR)^t} \right| = 0; \quad (11)$$

This high-level iterative process is described in Figure 4. Further information regarding the details of the different calculations for the internal loop is shown in Figure 5.

The OWCAT financial model for a generic offshore wind farm is displayed in Figure 5. Two main areas can be identified – the area outside the purple dashed lines, representing a standard corporate finance model based on P50 cash flows and the area inside the purple dashed lines, representing a part of a project finance model or what is referred in this paper as a Project Finance Add-in based on P90 cash flows. These P50 and P90 cash flows stem from the P50 and P90 AEP values which are the output of the Annual Energy Production module. These P50 and P90 AEP values come in turn from the estimated mean wind speed uncertainty, influenced by several uncertainty drivers. An LCOE value needs to be assumed in order to transform AEP values to revenue cash flows. This is represented in

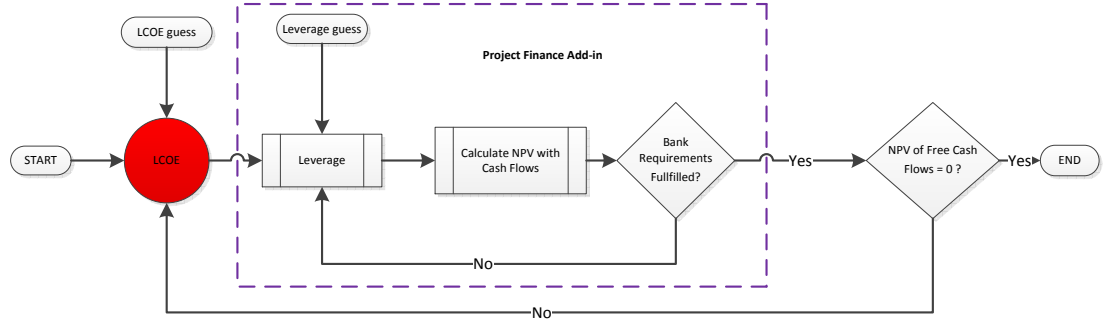


Figure 4: Double Loop Iterative Project Finance Modelling

Figure 5 by a red circle – value that changes from iteration to iteration until the numerical scheme converges (see figure above for the explanation on the two-fold iterative calculation).

The standard corporate finance model calculates the different variable cash flows that are required to work out the NPV of the project – seabed rent, fixed cash flows, construction and operational insurances and taxes. Given a discount rate, an iterative process is required to work out the LCOE that makes the cumulative free cash flows zero at the end of the project. The standard corporate finance calculation requires one iterative calculation, whereas the Project Finance Add-in adds an additional loop by working out the amount of debt that the financial institution provides to the project. In cases where the offshore farm is financed via corporate finance arrangements, only the left hand side of the financial model is needed. However, this paper’s objective is to understand the effect of the mean wind speed estimated uncertainty on debt sizing for offshore wind farms – so the full financial model needs to be taken into consideration.

The purpose of the Project Finance Add-in (displayed within purple dashed lines) is to estimate the amount of debt that can be reasonably supported by the project based on the probabilistic metric given by the P90 estimated mean wind speed. The output of the Project Finance Add-in is the Debt Finance, Operational and Construction Interest and the Financing Fees cash flows. Without the Project Finance Add-in it would not be possible to estimate the P90 cash flows that are required by the financial institution to support the non-recourse financing of the offshore wind farm. Cash flows in red are key to understand the effect of the estimated mean wind speed on debt sizing for offshore wind farms. These come into play from two sides. On the one side the development expenditure, which is influenced, to some extent, by the cost of the sensing device selected by the developer to characterise the wind speed uncertainty for a given site. On the other side, the changes on the financing costs represented by the four outputs from the Project Finance Add-in: the Debt Finance, Construction and Operational Interest and the Financing Fees. Given the iterative process of the financial modelling, these four cash flows are displayed in blue and are worked out via standard debt sculpting techniques.

It is important to bear in mind that when carrying out an offshore wind farm project evaluation via project finance arrangements, both areas of the financial model need to be taken into consideration. The Project Finance Add-in works out the Debt Finance, Construction and Operational Interest and Financing Fees P90 cash flows and the standard corporate finance calculates all the remaining P50 cash flows that are then fed into the NPV operator. Equation 12 splits the cash flows between these two P50 and P90 categories. Therefore, the developer selects a measuring campaign strategy to measure the mean wind speed estimated uncertainty which directly affects the  $FCF_t^{P50}$ . Equation 13 illustrates

that the P50 free cash flows are a function of the DEVEX incurred by the developer. At the same time, the mean wind speed estimated uncertainty, represented here with  $\sigma$ , has an indirect effect on the P90 free cash flows - the financing conditions such as Debt Finance, Construction and Operational Interest and Financing Fees cash flows. Equation 14 illustrates that the P90 free cash flows are a function of the mean wind speed estimated uncertainty.

This type of modelling integrates the wind resource assessment at the heart of the cost calculations through project finance constraints and allows to quantify and investigate the effect of the mean wind speed estimated uncertainty in debt sizing for offshore wind farms.

$$LCOE = \lambda \left| \sum_{t=1}^n \frac{FCF_t^{P_{50}} + FCF_t^{P_{90}}}{(1 + MARR)^t} \right| = 0; \quad (12)$$

$$FCF_t^{P_{50}} = FCF_t^{P_{50}}(DEVEX(\sigma)) \quad (13)$$

$$FCF_t^{P_{90}} = FCF_t^{P_{90}}(\sigma) \quad (14)$$



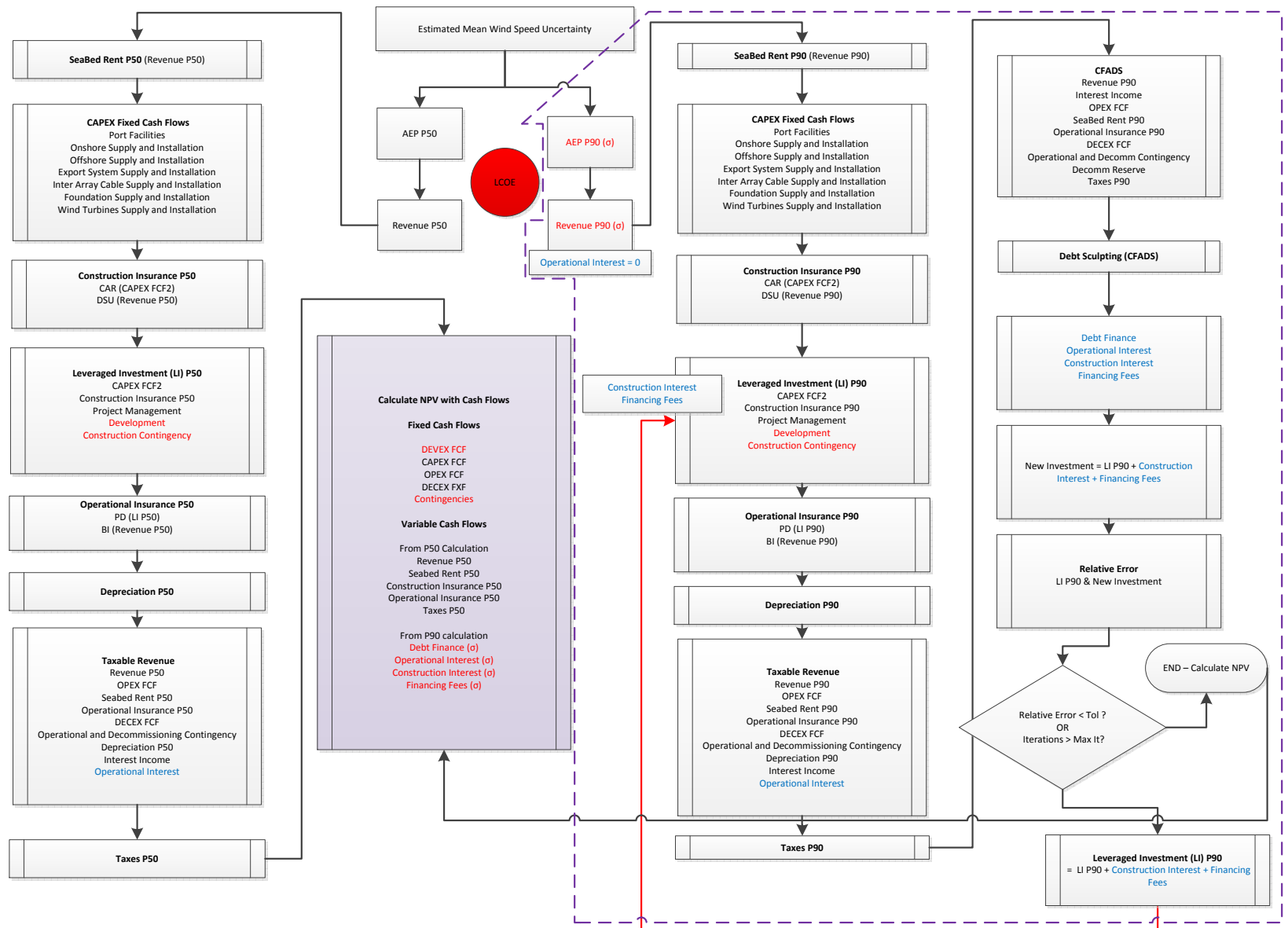


Figure 5: Project Finance Structure within Cost Modelling Tool

## 5 Relationship between Mean Wind Speed Estimated Uncertainty and Debt Sculpting

This section builds on Section 4 to derive some theoretical relationships between the mean wind speed estimated uncertainty and the debt sculpting, which gives rise to the curves depicted in Figure 6. Figure 6 is used as a reference figure for this section. Let us put aside the red lines for the moment. The top right chart shows the relationship between the DEVEX and the uncertainty in the mean wind speed. Longer wind campaigns and the use of more precise sensing devices allow for a reduction in uncertainty; however, this comes at a cost. A met mast is much more expensive than a Floating LIDAR, which in turn is much more expensive than mesoscale modelling. However, mesoscale modelling is much less precise than a Floating LIDAR, which itself is less precise than a met mast. In general, higher development expenditure results in a decrease in uncertainty. Also, in general, uncertainty is dependent on the quality of the resulting data and the successfulness of the campaign. However, for the sake of simplicity, it is assumed that all campaigns are equally successful, with high availability of data.

The top left chart shows the theoretical relationship between the  $AEP_{P90}$  and the uncertainty in mean wind speeds. As the uncertainty decreases, the  $v_{P90}$  and the  $AEP_{P90}$  increases. This relationship is a direct consequence of what has been displayed in Figure 1, where a smaller  $\sigma$  would give higher values of  $v_{P90}$ . It is worth keeping in mind that all the other factors affecting the AEP have been kept constant here.

Two constraints imposed by banks are applied: the maximum gearing and the DSCR. For further details and description of these terms, see Section 2 above. Consider an offshore wind project for which the binding constraint on debt sizing is the DSCR. As we have seen in the previous section, a limitation on the DSCR can be translated into a limitation on the gearing. If the gearing obtained by the DSCR is lower than the maximum gearing allowed by the bank, this means that extra money could be lent if the CFADS increased. The CFADS is directly related to the wind speed uncertainty as the revenue stream calculated by the banks is based on a  $AEP_{P90}$ . Consequently, when the mean wind speed estimated uncertainty is reduced, a higher CFADS becomes available, and this in turn increases the gearing. The bottom left chart shows the relationship between gearing and uncertainty in the estimated mean wind speed. As can be seen in the same chart, the project reaches a point where a further reduction in uncertainty does not give rise to a higher gearing - this uncertainty threshold is defined as  $U^*$ . Reaching  $U^*$  means that the maximum gearing has been met.

The bottom right chart combines the rest of the charts to calculate the LCOE as a function of the mean wind speed uncertainty. This chart can be divided into two regions. The first region has values of uncertainty higher than  $U^*$ . In this case, a higher development expenditure gives rise to a reduction in uncertainty, which increases the  $AEP_{P90}$ . That means that a higher gearing can be obtained, decreasing the LCOE. In the second region, to the left of  $U^*$ , higher development expenditures also lead to higher  $AEP_{P90}$ . However, in this case, since the project is limited by the maximum gearing, no extra gearing is reached. As we reduce the uncertainty further there is an increase in the development expenditure but this does not lead to more favourable financial conditions. The LCOE therefore increases as mean wind speed uncertainty is reduced.

In the above,  $U^*$  is the optimal level of uncertainty. However, for some projects, it may be optimal to choose a higher level of uncertainty, depending on how sensitive variations or incremental costs and AEP values are to uncertainty. As an example, consider the red lines in Figure 6. These exemplify a project not limited by the maximum gearing. For this project, an increase in the DEVEX still leads to an increase in the  $AEP_{P90}$ . As a result better financing conditions are reached. But despite this, the LCOE reaches an optimal before the maximum gearing is obtained. The reason for this may be, for instance, that the increase in DEVEX is not compensated by the estimated resource.

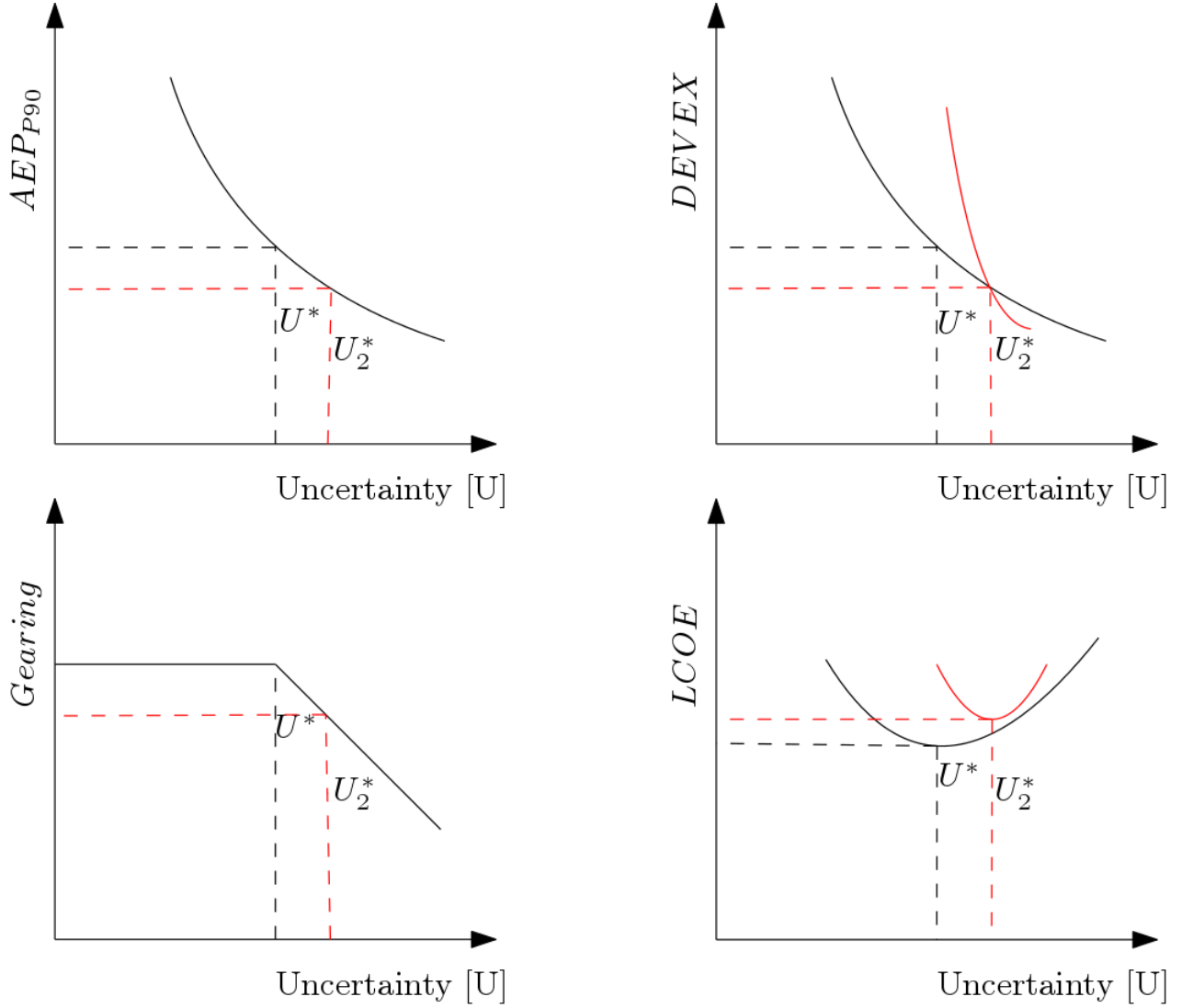


Figure 6: Theoretical mean wind speed uncertainty -  $AEP_{P90}$ ,  $DEVEX$ ,  $Gearing$  and  $LCOE$  curves, all the other factors being equal

In this case,  $U_2^* > U^*$  is the optimal amount of uncertainty. In general, whatever the characteristics of the sensitivities of  $DEVEX$  and financing costs to uncertainty, it is never optimal to reduce uncertainty below  $U^*$ . This conventional wisdom that better mean wind speed predictions are always worth the increased development expenditure is not true. The next section considers cost modelling for real offshore wind farm projects, where these relationships in Figure 6 are investigated.

## 6 Case Study

The average size of European commercial offshore wind farms commissioned in the year 2017 is 500 MW [2]; we therefore chose the same size as a reference in our case study. The case study is based on three commercial offshore wind farms with the following characteristics: Project A represents our reference offshore wind farm, which is representative of UK round 2 offshore wind projects. Project B represents an offshore wind farm located near the coast, meaning that only a relatively small amount of CAPEX is required to develop the project. However, it is assumed that the site has a poorer wind resource. Finally, Project C represents an offshore wind farm located very far from shore. Project C has a high CAPEX, but it also has access to higher wind resource than previous A and B projects. To some extent, Project C is representative of German offshore wind farms. All projects are assessed with a generic 8.3 MW wind turbine with a rotor diameter of 164 m. We also assume, for the sake of simplicity, that the export cable length, construction and operational port distances are equal to the distance from shore. Whereas Project A and B wind turbines are commissioned atop monopile foundations, project C uses jackets due to water depth requirements. The project specifications of the offshore wind farms are shown in Table 2.

Parameter	Project A	Project B	Project C
Water Depth [m]	25	15	40
Distance from shore [km]	25	15	100
Wind Speed @ 100m [m/s]	9	8	10
Foundation Type	Monopile	Monopile	Jacket
Electrical Infrastructure	High Voltage Alternating Current (HVAC)	HVAC	HVAC
Wind Turbine Type	164-8.3 MW	164-8.3 MW	164-8.3 MW
CAPEX [2015/kW]	2600	2500	3300
OPEX [2015/kW/yr]	85	80	100

Table 2: Project A, B and C specifications

The modelling approach to offshore wind cost analysis presented in this paper is based around Offshore Wind Cost Analysis Tool (OWCAT) developed at the EDF Energy R&D UK Centre. Further information on the tool can be found in Section 3 as well as [20]. The only parameters that are modified within the tool are the development expenditure and the uncertainty in the estimated mean wind speed (apart from the site specifications for the different cases). All other uncertain parameters such as the availability of the offshore wind farm, wake losses, are assumed to be the same in all three cases. We also assume that the availability of the offshore wind farm does not depend on the distance from shore, and therefore, that the technical performance of project A, B and C is similar.

In order to reflect the recent changes in financing conditions displayed in Table 1, we consider two scenarios. The first scenario assumes a gearing representative of the period between 2014 and 2015 (70:30). A second scenario is representative of more recent gearings (75:25).

The aim of the current paper is to reflect the changes of the mean wind speed estimated uncertainty in the LCOE, and not to analyse detailed site-specific uncertainties. In consequence, the emphasis has been placed on the choice of measurement devices, which developers face once a site has been selected. Individual devices are assumed to be deployed in the centre of the offshore wind farm so as to avoid comparisons that favour horizontal extrapolations above others. In this case study, the developer considers the following available options to assess the wind speed of projects A, B and C. A Hub Height Met Mast (HHMM), a Below Hub Height Met Mast (BHHMM) that has a shorter mast than HHMM, a High Accuracy Commercial Floating LIDAR (HAFLIDAR), a Low Accuracy Commercial Floating

LIDAR (LAFLIDAR) and Mesoscale modelling are assumed. Mesoscale modelling is considered as a service provided to the developer. Table 3 shows the respective costs of these methods. The difference between HHMM and BHHMM is the cost of having a taller mast, which allows wind speeds to be measured closer to hub height. The difference between HAFLIDAR and LAFLIDAR is their degree of precision. The developer may opt for a cheaper and less precise device or for a more expensive and precise one.

Cost [£m 2017]	HHMM	BHHMM	HAFLIDAR	LAFLIDAR	Mesoscale
DEVEX	10	9	1.2	1	0.15

Table 3: Development expenditure for the different wind measurement campaigns

These cost estimates have been derived from [22] [23] [24][30][25] as well as from discussion with experts in the field of wind resource assessment. If bigger offshore wind farms were to be analysed, then economies of scale in the cost of the devices should be considered as reflected in [26].

In order to represent current technology trends, and given that the first offshore wind project to be built using the  $AEP_{P90}$  on wind resource data from a Floating LIDAR was Burbo Bank Extension in the UK, in 2014 [27], two different types of Floating LIDAR are considered in this study. According to the Carbon Trust Offshore Wind Accelerator [25], a pre-commercial LIDAR has an indicative measurement uncertainty range between 4 to 7%, whereas a commercial one can achieve a range between 2 to 4%. The Floating LIDAR industry has benefited from research and development programmes and has reached the commercialisation stage [28][29] [30]. This is the reason why two commercial LIDARs are considered. More recently, it was announced that AXYS FLIDAR met the commercialisation stage of the Carbon Trust Offshore Wind Accelerator [31], meaning that uncertainties between 3 and 4% in instrument accuracy for a Floating LIDAR is a sensible choice according to the current state of technology.

A section on the classification and description of wind speed uncertainties is out of the scope of this research paper, however wind speed uncertainties have been estimated based on the classification provided by DNV GL [32] [7] and [30] as well as discussions with industry experts. Those values are displayed in Table 4. The different site-specific uncertainties for A, B and C are shown in Table 5 and are independent of the device. Table 6 shows the devices ordered in terms of total precision, HHMM is the most precise one (4.25%) and Mesoscale the less precise (10.84%). All uncertainties are expressed as a percentage of the standard deviation of the mean wind speed and are combined by assuming they are independent and normally-distributed.

The relationship between cost and mean wind speed estimated uncertainty for the different campaigns is given in Figure 7. It is shown that this relationship follows a negative concave trend hypothesised in Section 5 on the top right of Figure 6.

Uncertainty [%]	HHMM	BHHMM	HAFLIDAR	LAFLIDAR	Mesoscale
Instrument Accuracy	2	2	3	4	10
Measurement Interference	1.5	1.5	0.5	0.5	0
Data Quality & Metadata	1	1	1	1	0
Vertical Extrapolation	0	1	0	0	3
Horizontal Extrapolation	1.5	1.5	1	1	0
Total Wind Speed Measurement	3.08	3.24	3.35	4.27	10.44

Table 4: Breakdown of the device-specific uncertainties for the different measurement campaigns, based on DNV GL [33], [7] and [30]

Description for A, B and C Projects	Uncertainty [%]
Representativeness of Data Period	1.5
Consistency & Quality of Reference Data	1
Correlation	0.5
On-site data	0.5
Wind Frequency Distribution - Past	0.5
Wind Frequency Distribution - Future	0.5
Inter-annual Variability (IAV) of the Wind - Future	1.5
Climate Change	1.5
Total Site	2.92

Table 5: Breakdown of the site-specific uncertainties for the different measurement campaigns [33]

Uncertainty [%]	HHMM	BHHMM	HAFLIDAR	LAFLIDAR	Mesoscale
Total Wind Speed	4.25	4.36	4.45	5.17	10.84

Table 6: Breakdown of the total uncertainties for the different measurement campaigns

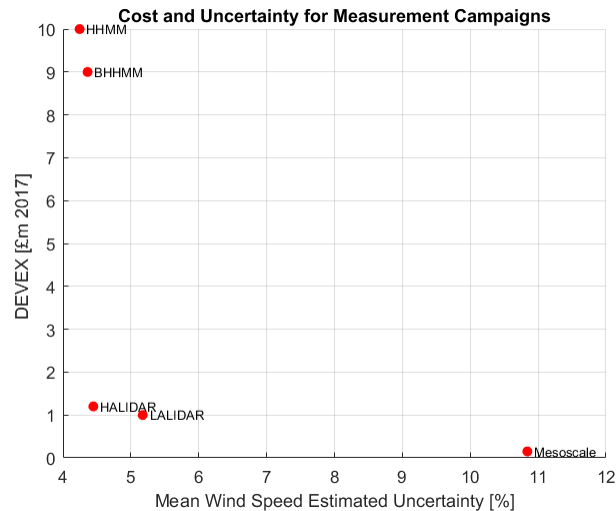


Figure 7: Relationship between DEVEX and Wind Speed Measurement Uncertainty for Different Wind Measurement Campaigns

The case study consists on selecting the sensing device that minimises the LCOE, which is a real-world problem faced by developers in the offshore wind industry. Three representative commercial offshore wind farms are selected whose characteristics are shown in Table 2. These sites attempt to be representative for different types of site-specific characteristics. Five commercial sensing devices are available for conducting the wind campaigns, capturing well established devices such as met masts and the latest developments in FLIDAR technology. In addition, two scenarios are assumed with different gearing regimes, that reflect a reduction on the perceived risk from financial institutions when investing in offshore wind.

### 6.1 Scenario 1: Maximum gearing of 0.70

Figure 8 shows the first set of results, assuming 0.70 maximum gearing. All charts show the relationship between the uncertainty in the estimated mean wind speed (on the horizontal axis), the gearing (the right vertical axis) and the LCOE (the left vertical axis) for all three projects. The continuous black line depicts the gearing for different levels of uncertainty, whereas the dashed red line highlights the lowest LCOE that can be achieved in each project.

Starting off with the Mesoscale Modelling campaign on the right in all three projects, none of the projects are limited by the gearing and hence a further reduction in uncertainty may lead to a reduction in financing costs that more than compensates the higher development expenditure. In all projects, using LAFLIDARs allows the developer to reach the point where projects become limited by the gearing. Although HAFLIDARs are more precise than LAFLIDAR, they are not the optimal choice, since the further reduction in uncertainty they achieve do not decrease financing costs, while they do increase development expenditure.

In all cases, the optimal device is the LAFLIDAR. A slightly higher LCOE is obtained by using a HAFLIDAR. The slopes of maximum gearing are affected by the type of offshore wind farm. Higher wind resource results in flatter slopes for the maximum gearing, whereas poor wind results in steeper slopes. Project B has a lower CAPEX and lower wind resource than the other projects. For this reason, the maximum gearing of the project is achieved with a lower uncertainty, since the effect of improving financing conditions by reducing the uncertainty is weaker. Project C, with high CAPEX and a high wind resources, achieves maximum gearing at a higher uncertainty, since the effect of improving the financing conditions by reducing the uncertainty is stronger – for the same level of uncertainty, a higher level of production can be obtained.

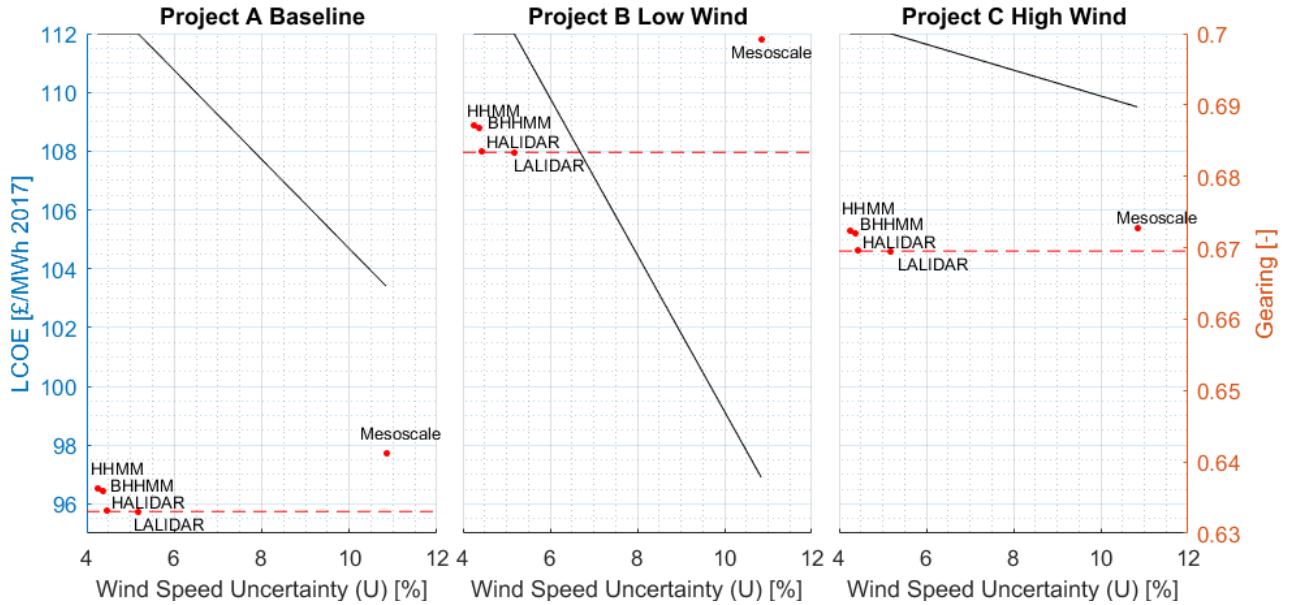


Figure 8: Project A, B and C relationship between Uncertainty, Gearing and LCOE for a maximum gearing of 0.70



## 6.2 Scenario 2: Maximum gearing of 0.75

Figure 9 shows the results of a similar exercise, but with a more recent gearing of 0.75. As above, all charts show the relationship between the uncertainty in the estimated mean wind speed (on the horizontal axis), the gearing (the right vertical axis) and the LCOE (the left vertical axis) for all three projects. The continuous black line depicts the gearing for different levels of uncertainty, whereas the dashed red line highlights the lowest LCOE that can be achieved in each project.

The main difference with the previous results is that the point where project A becomes limited by the gearing has moved from the LAFLIDAR to the BHHMM. However, given the unfavourable trade-off between uncertainty and DEVEX, the HAFLIDAR is the optimal choice. Project B, characterized by a poor wind resource, also does not reach maximum gearing, with the HAFLIDAR being LCOE optimal. In both cases, this happens because of the steep slope of the trade-off between DEVEX and uncertainty as displayed in Figure 7. If the developer wants to slightly reduce the uncertainty from HAFLIDAR, a very large increase in DEVEX is incurred. In Project C the maximum gearing of the project is achieved with a higher uncertainty, since the effect of improving the financing conditions by reducing the uncertainty is stronger, and therefore the project also reaches its minimum LCOE with a HAFLIDAR.

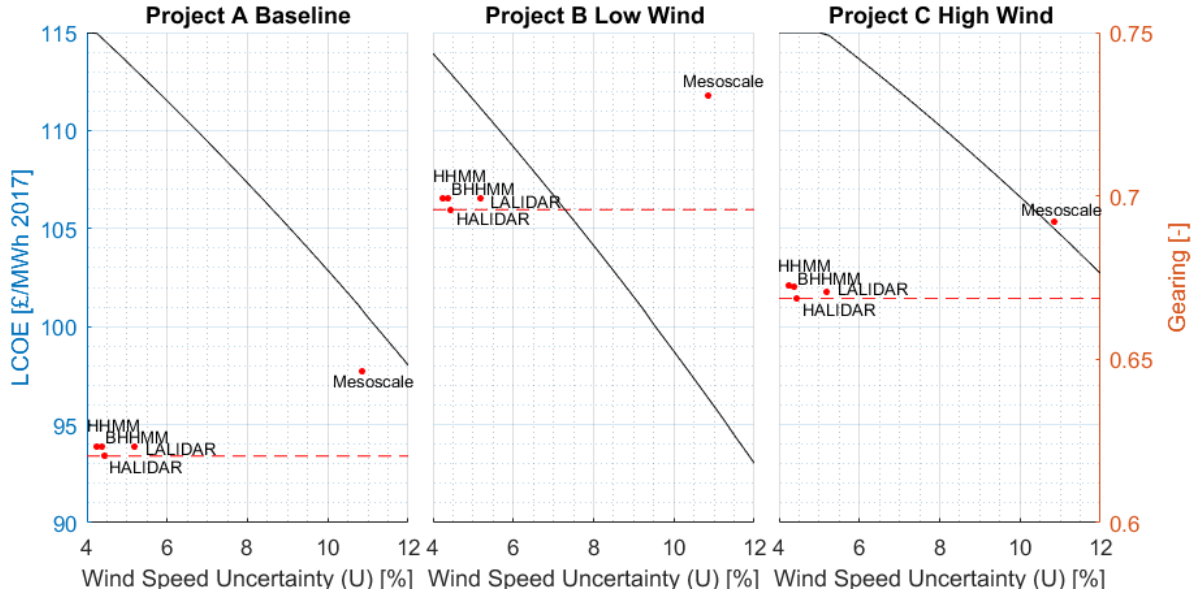


Figure 9: Project A, B and C relationship between Uncertainty, Gearing and LCOE for a maximum gearing of 0.75

## 7 Conclusions

We have shown that offshore wind projects can be categorised into two different types, based on project finance conditions. The first type is limited by the DSCR, whereas the second is limited by the maximum gearing offered by the bank. For projects limited by the maximum gearing the costs of decreasing mean wind speed uncertainty only increase the LCOE, whereas for projects limited by the DSCR the effect of decreasing the LCOE depends on the trade-off between the DEVEX and the mean wind speed estimated uncertainty. This is represented in Figure 7 and more theoretically on the top right of Figure 6. This means that it is never optimal to reduce uncertainty as far as possible, as it is commonly believed in the industry.

In a realistic case study, we have further explored this effect. Interestingly, this case study suggests that it is never optimal to use met masts to obtain the most reliable mean wind speed estimates. Commercial LIDARs are optimal in all cases, highlighting the maturation phase of this technology. Differences between different offshore wind farms specifications are reflected in the slope of the gearing and the point at which maximum gearings are reached. High wind resource offshore wind farms will have higher gearings than other average-wind farms for the same level of uncertainty. Conversely, poor wind resource offshore wind farms may not reach the gearing limit or reach it for smaller levels of uncertainty than average-wind farms.

In addition, the maximum gearing has a big effect on the financial conditions and on optimal wind speed estimation techniques. As we have seen, the maximum gearing is increasing, as banks are becoming more familiar with offshore wind projects. This means that additional measurements become more valuable. In our case study, the optimal device for a maximum gearing of 0.75 is the more precise and expensive HAFLIDAR, whereas for a gearing of 0.70 it is the cheaper and less precise LAFLIDAR. This illustrates that a detailed understanding of project finance constraints is necessary to optimally plan and execute offshore wind projects.

This paper has presented the development of a novel theoretical cost modelling framework which includes detailed considerations of financing requirements that until now have been usually ignored in the offshore wind planning models. The methodology presented here links these financing requirements such as the DSCR and the maximum gearing to the cash flow metrics, while considering the development expenditure incurred in choosing a wind speed measurement device and its mean wind speed estimated uncertainty represented by the P50 and P90 metrics. This methodology can be applied to any existing standard corporate finance cost model to account for project finance arrangements. At the same time, this cost modelling framework allows policy-makers and developers alike to assess the trade-off between DEVEX and the estimated wind speed uncertainty, leading to more informed decision that have the potential to drive down the cost of energy.

It has been assumed in this study that the DSCR metric is based on P90 cash flows. However, in reality, projects might be evaluated against two DSCRs metrics based on P50 and P90 cash flows; this imposes an additional constraint. Further work should include the ability to incorporate these two constraints as well as a description of the different uncertainties that characterise the mean wind speed and energy factors.

## 8 Acknowledgements

This article is based on work sponsored by EDF Energy R&D UK at the Industrial Doctoral Centre for Offshore Renewable Energy (IDCORE), a consortium of the University of Exeter, University of Edinburgh and University of Strathclyde. IDCORE is funded by both the Energy Technologies Institute and the Research Councils Energy Programme through grant number EP/J500847/1. Additional

support came from the UK Engineering and Physical Sciences Research Council through grant number EP/P001173/1 (CESI). Special thanks go to Hugo Herrmann for reading the manuscript and for his constructive suggestions.

## References

- [1] Bjarne Steffen. “The importance of project finance for renewable energy projects”. In: *Energy Economics* 69 (2018), pp. 280–294. ISSN: 0140-9883. DOI: 10.1016/j.eneco.2017.11.006. URL: <https://doi.org/10.1016/j.eneco.2017.11.006>.
- [2] Wind Europe. *Financing and investment trends: The European wind industry in 2017*. Tech. rep. 2018, p. 32. DOI: 10.1080/00218460701751855. URL: <https://windeurope.org/wp-content/uploads/files/about-wind/reports/Financing-and-Investment-Trends-2017.pdf>.
- [3] IEA - RETD Renewable Energy Technology Deployment. *Gusts of change: How effective policy is catalysing a booming offshore wind sector*. Tech. rep. March. 2017.
- [4] Wind Europe. *Offshore Wind in Europe: Key Trends and Statistics 2017*. Tech. rep. 2018.
- [5] Achim Schreider and Mirko Sedlacek. “Project Financing Offshore Wind Farms: Risk Analysis for a Structured Finance”. In: *European Offshore Wind 2009 Conference*. Stockholm, 2009, pp. 1–10.
- [6] David Wadham. *Financing Offshore Wind: Plain sailing?* Tech. rep. 20. 2018.
- [7] D Foussekis et al. “Uncertainty estimations for offshore wind resource assessment and power verification”. In: *EERA DeepWind 18*. Trondheim, 2018.
- [8] Angeliki Loukatou et al. “Stochastic wind speed modelling for estimation of expected wind power output”. In: *Applied Energy* 228.May (2018), pp. 1328–1340. ISSN: 03062619. DOI: 10.1016/j.apenergy.2018.06.117. URL: <https://doi.org/10.1016/j.apenergy.2018.06.117>.
- [9] Anthony Crockford et al. *Estimated uncertainty for various wind measurement strategies including floating LiDAR at the Hollandse Kust Zuid offshore wind farm zone*. Tech. rep. 2016.
- [10] Jie Yan et al. “Uncertainty estimation for wind energy conversion by probabilistic wind turbine power curve modelling”. In: *Applied Energy* 239.September 2018 (2019), pp. 1356–1370. ISSN: 03062619. DOI: 10.1016/j.apenergy.2019.01.180.
- [11] Gavin Smart. *Offshore Wind Cost Reduction: Recent and future trends in the UK and Europe*. Tech. rep. November. 2016, pp. 1–10.
- [12] BVG associates. *Future renewable energy costs: offshore wind*. Tech. rep. 2017, p. 80.
- [13] Varvara Mytilinou and Athanasios J. Kolios. “Techno-economic optimisation of offshore wind farms based on life cycle cost analysis on the UK”. In: *Renewable Energy* 132 (2019), pp. 439–454. ISSN: 18790682. DOI: 10.1016/j.renene.2018.07.146. URL: <https://doi.org/10.1016/j.renene.2018.07.146>.
- [14] Anastasia Ioannou, Andrew Angus, and Feargal Brennan. “A lifecycle techno-economic model of offshore wind energy for different entry and exit instances”. In: *Applied Energy* 221.November 2017 (2018), pp. 406–424. ISSN: 03062619. DOI: 10.1016/j.apenergy.2018.03.143. URL: <https://doi.org/10.1016/j.apenergy.2018.03.143>.
- [15] EDHEC Infrastructure Institute-Singapore. *Cash Flow Dynamics of Private infrastructure Project Debt*. Tech. rep. March. 2016, pp. 1–108.
- [16] Green Giraffe. *Project finance for German offshore wind*. Tech. rep. February. 2017.
- [17] Edward Bodmer. “Debt Sculpting in a Project Finance Model”. In: *Corporate and Project Finance Modeling. Theory and Practice*. 2015. Chap. 41, pp. 515–537. ISBN: 9781118854365. DOI: 10.1002/9781118957394. URL: <https://drive.google.com/open?id=0B544TwTVwnWkN2Z1Sm9YZHZxSG8>.
- [18] Green Giraffe. *Offshore wind finance – evolution and outlook*. Tech. rep. September. 2017.
- [19] Green Giraffe. *Introduction to wind project finance*. Tech. rep. March. 2017.
- [20] Esteve Borrás Mora. “Transition from Deterministic to Stochastic Cost Models for Offshore Wind Farms”. In: *Offshore Wind Energy Conference*. June. 2017.

- [21] Mark J. Kaiser and Brian F. Snyder. *Offshore wind energy cost modeling- Installation and de-commissioning*. 2012, 248 pp. ISBN: 9781608052851. DOI: 10.2174/97816080528511060101. URL: <http://www.benthamdirect.org/pages/content.php?9781608052851>.
- [22] Peter Clive et al. *Offshore Power Curve Tests for Onshore Costs : A Real World Case Study*. Tech. rep. 2014, pp. 1–9. DOI: 10.1177/1066480709355039.
- [23] BVG Associates. *Value breakdown for the offshore wind sector*. Tech. rep. February. 2010, pp. 1–20. URL: [https://www.gov.uk/government/uploads/system/uploads/attachment\\_data/file/48171/2806-value-breakdown-offshore-wind-sector.pdf](https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/48171/2806-value-breakdown-offshore-wind-sector.pdf).
- [24] G.A.Cool. “Floating LiDAR technology: Oceanographic parameters influencing accuracy of wind vector reconstruction”. PhD thesis. 2016.
- [25] Carbon Trust. *Carbon Trust Offshore Wind Accelerator Program*. Tech. rep. 2017. URL: <https://www.carbontrust.com/offshore-wind/owa/>.
- [26] Electricity Market Reform. “Supply Chain Plan Consultation”. In: November (2013).
- [27] Offshorewindbiz. *Burbo Bank Extension First FLiDAR-Calculated OWF to Be Built*. 2015. URL: <https://www.offshorewind.biz/2015/04/24/burbo-bank-extension-first-flidar-calculated-owf-to-be-built/>.
- [28] J. Gottschall et al. “Results and conclusions of a floating-lidar offshore test”. In: *Energy Procedia* 53.C (2014), pp. 156–161. ISSN: 18766102. DOI: 10.1016/j.egypro.2014.07.224. URL: <http://dx.doi.org/10.1016/j.egypro.2014.07.224>.
- [29] Julia Gottschall et al. “Floating lidar as an advanced offshore wind speed measurement technique: current technology status and gap analysis in regard to full maturity”. In: *Wiley Interdisciplinary Reviews: Energy and Environment* 6.5 (2017). ISSN: 2041840X. DOI: 10.1002/wene.250.
- [30] Hugo Herrmann et al. “Floating LiDAR Uncertainty Assessment Wind Europe – Resource Assessment March 2017”. In: March. 2017.
- [31] Offshorewindbiz. *Axys FLIDAR Reaches Stage 3 on Carbon Trust Roadmap*. 2018. URL: <https://www.offshorewind.biz/2017/06/06/axys-flidar-reaches-stage-3-on-carbon-trust-roadmap/>.
- [32] DNV KEMA ENERGY & SUSTAINABILITY. *Framework for the Categorisation of Losses and Uncertainty for Wind Energy Assessments*. Tech. rep. 2013. URL: <http://www.sgurrenergy.com/wp-content/uploads/2013/02/Loss-and-Uncertainty-Definitions-Report-05Feb2013.pdf>.
- [33] DNV GL. *Study on UK Offshore Wind Variability*. Tech. rep. L2C124303-UKBR-R-01, Issue B. 2016.